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A New Personnel Selection Model for Quality Positions

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Abstract

Quality Management System (QMS) plays a crucial role in each company that aims to gain a competitive advantage. However, the QMS implementation requires a competent staff. Therefore, companies need a tool that will help them select the most competent candidates for quality positions. To this aim, we have developed a new fuzzy hybrid approach based on the integration of the 2-tuple linguistic representation model with the Distance to the Ideal Alternative (DIA) method, which enables assessing candidates without distortion of the initial information. In this article, we present an illustrative example of ranking candidates for a quality coordinator position to demonstrate the validity and efficiency of our approach. In addition, we compare our approach with the most well-known and used classification approach, which is based on the use of the TOPSIS method.

Keywords: Competence, 2-tuple, DiA method, Multiple criteria decision-making, Quality management system, QMS, Personnel selection.

1 | Introduction

Technological development, diversity of products and services, and industrial market competition have all urged companies to adopt management that will ensure resilience in the competitive market, unlock operational excellence, and help improve competitiveness in the market. For this purpose, several authors have integrated competence into industrial management, known as competence management, which has an essential impact on industrial performance. Among these authors, we cite Barney and Zajac [1], who maintain that the competitive advantage of a company lies in its competencies, and Stepanenko and Kashevnik [2], who argued that competence management has become a crucial process for any company that aims at stabilizing its economy. The search for key competencies, Core competencies, is relevant research for companies that attempt to have a competitive,

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sustainable advantage, as is well shown by the authors Lamarque [3] and Retour [4]. In short, competence management has always been an intriguing area for researchers, and several authors have striven to analyze, study, and understand this subject. We, in turn, have been oriented towards competence management, especially after the release of the latest version 2015 of ISO 9001 [5], which granted great importance to competence management in the quality field.

The introduction of the competence approach in the industrial sector began in the early 1970s and has since become an extremely popular approach. McClelland [6] proposed introducing the term "competence" to the human resources literature to assist the United States Information Agency in improving its selection procedures. Undoubtedly, competence has become the focal point of discussions in human resources management, emerging as a critical strategy for effective performance. For instance, Klemp [7] and Boyatzis [8] define competence as an underlying characteristic leading to superior performance in a job. Spencer Lyle and Spencer Signe [9] defined competencies as the combination of underlying attributes, skills, traits, knowledge, and motivations of a person causally related to superior performance in a job. Le Boterf [10] asserts that competence is the mobilization or activation of multiple knowledge in a given situation and context. Lucia and Lepsinger [11] defined competence as a set of related knowledge, skills, and attitudes that affect a significant part of a person's work (a role or responsibility), correlated with job performance, measurable against accepted standards, and improvable through training and development. Gunawan et al. [12] view competencies as a set of interdependent knowledge, characteristics, attitudes, and skills that have a significant impact on human resources and their behavior, correlated with individual job performance, assessable by acceptable standards, and improvable through training and development.

In terms of modeling, competence was described by Miranda et al. [13], emphasizing that the key points for modeling competence are the two terms: competency and competence. A competency represents all forms of knowledge, skills, attitudes, and capacities. In contrast, competence is a set of competencies that take into account the context of an acquisition, with the possibility of evaluating its level of acquisition according to a given scale [14]. In our research, we are interested in the concept of competence. This concept is polysemic and transdisciplinary [15]. It is comprised of three levels: individual, collective, and organizational [16], [17]. The three competence levels are not independent. Studies on the subject reveal that collective competence can only be defined if individual competence is recognized and that the organization can only acquire high-level competencies if it has a high level of individual competencies. The importance of individual competence leads us to focus our research on individual competence management. The latter is considered an organizational perspective since it is a management that provides a set of processes and a methodological framework to develop the competencies required to achieve the company's objectives. In general, the roles of competence management are: 1) identification of skills, knowledge, behaviors and abilities that satisfy current and future needs related to personnel selection, taking into account the organization's strategies and priorities [11], 2) assessment of the personnel's acquired competences, 3) personnel development [18] to improve employees' competences [19] and eliminate gaps between required and acquired competences, 4) enhancement of knowledge sharing [20], and 5) facilitation of self-assessment.

In fact, several studies, such as those by Tena and Llusar [21], have addressed the assessment of quality in the industrial sector. However, the assessment of individual competencies related to the quality field has not been addressed in scientific research. The present work is part of this context. It aims to develop a model to assess acquired competencies related to quality, which is an essential step for any company wishing to recruit qualified personnel and to identify its available human potential. This model defines competence as the mobilization of a set of knowledge, know-how, and know-whom acquired by an individual to perform a specific task, taking into account the objectives of the company and its context. Why choose the quality management system, and why have we focused our research on the assessment process?

2 | Related Work

The Quality Management System (QMS) is a system that consists of directing the knowledge of personnel sand employees as well as controlling organizational and operational processes to achieve the expected quality objective and to improve the company's performance in meeting customers' product and service expectations. Oakland [22] claimed that organizations that implement total quality management improve flexibility, efficiency, and competitiveness. The International Organization for Standardization (IOS) 9001, in its latest 2015 version [5], supports the critical role of personnel competence management in QMS implementation and achieving expected organizational performance. In the literature, there are some works on the process of assessment and selection of personnel related to quality, such as Saremi et al. [23] and Zolfani et al. [24], and on the assessment of organizational competencies, such as Tena and Llusar [21], but to meet the requirements of the ISO standard 9001:2015, each company needs a tool or process to assess the individual competencies necessary to manage a QMS while taking into consideration the organizational context and subjective judgment of the experts. In order to achieve this, we have developed a competence assessment process that helps companies evaluate their staff and select the best candidate for a quality position.

Before proposing our approach, we present a literature review on personnel selection in the following lines. Wu et al. [25] pointed out that "The personnel selection problem, which is a significant topic for organizations' success, belongs to an Multi-Criteria Decision-Making (MCDM) problem". In the literature, a variety of MCDM methods are used to solve personnel selection problems. For example, Lin [26] proposed a personnel selection approach based on the integration of the Atrial Natriuretic Peptide (ANP) and the fuzzy Data Envelopment Analysis (DEA) methods. Kabak [27] combined the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method and the fuzzy ANP method for solving the personnel selection problem. Rouyendegh and Erkan [28] adopted the fuzzy ELimination and Choice Expressing REality (ELECTRE) method to select academic personnel. Salehi [29] integrated the Analytic Hierarchy Process (AHP) method with the Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR) method for solving the personnel selection problem. Esmaili Dooki et al. [30] Integrated fuzzy AHP and fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methods for selecting chief bank inspectors.

The integration of three methods, Fuzzy Decision Making Trial and Evaluation Laboratory (FDEMATEL), Fuzzy Analytic Hierarchy Process (FAHP), and FVIKOR, has been applied by Taati and Esmaili Dooki [31] to rank and select the best hospital nurses of the Year. Urosevic et al. [32] integrated the SWARA method with the WASPAS method to select personnel in the tourism sector. Jasemi and Ahmadi [33] proposed a personnel selection approach based on the fuzzy ELECTRE method. The Encephalo Duro Arterio Synangiosis (EDAS) method was adopted by Karabasevic et al. [34] to select personnel in the information technology industry. Chang [35] developed a collaborated MCDM model for selecting professional gamers in the e-sports industry. Chuang et al. [36] used the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE-AS) method to calculate the gaps between the current level and the aspirational level for each candidate and to rank the candidates. Wu et al. [25] used the TOPSIS method to rank and select the optimal hosts of variety shows for television stations in the social media Era.

Popović [37] developed a personnel selection model based on the SWARA and COmbined COmpromise SOlution (COCOSO) methods. Lim et al. [38] applied the AHP and TOPSIS methods to help a company select livestreamers. Nong and Duc-Son [39] proposed the integration of AHP and TOPSIS methods for the selection of qualified personnel. Uslu et al. [40] proposed integrating the Fuzzy AHP and MULTIOMOORA methods to select a qualified health manager. A combination of three MCDM methods (DEMATEL, ANP, and TOPSIS) was developed by Chiu et al. [41] to help a company's executives select the best podcaster. Ebrahimi et al. [42] developed a fuzzy similarity method based on TOPSIS for selecting personnel. Recently, some authors have presented the subjective preferences of evaluators with fuzzy sets such as Interval-Valued

Fuzzy Numbers (IVFN), grey numbers, Intuitionistic Fuzzy Numbers (IFNs), Hesitant Fuzzy Linguistic Term Sets (HFLTSs), and 2-tuple.

In recent years, to solve the problem of personnel selection, several authors have used an approach based on the integration of the 2-tuple representation model and the TOPSIS method; we cite in particular the works of Dursun and Karsak [43] and Raoudha et al. [44]. For our study, we developed a new approach based on the integration of the 2-tuple linguistic representation model and the DIA method to solve the problem of evaluating and ranking candidates for quality positions. This approach will be detailed in the next section.

3 | the Approach for Assessing the Acquired Competences Related to Quality

The need to develop a tool that will help recruiters assess and select competent candidates for quality positions led us to propose our approach, which is based on the integration of the 2-tuple and the DIA method. The proposed approach is based on three main steps shown in *Fig. 1*: identification of the required competencies, evaluation of the candidates' acquired competencies, and ranking of candidates.

3.1 | Identification of the Required Competencies Related to Quality

In general, the first step in the selection of candidates is to identify the required competencies. For this purpose, we applied the model of Ait Bahom et al. [45] to establish a framework of required competencies based on the requirements of the ISO 9001:2015 standard by grouping each competence into three categories: knowledge, know-how, and know-whom. *Table 1* presents an extract of the framework of required quality coordinator competencies.

3.2 | Evaluation of the Acquired Competences Related to Quality

Some authors, such as Santandreu-Mascarell et al. [46], have conducted a qualitative study to assess individual competencies. To assess the acquired competencies by handling the subjectivity of evaluators' judgments, we chose to adopt the 2-tuple linguistic representation model. The 2-tuple linguistic representation model, proposed by Herrera and Martínez [47], is based on the concept of symbolic translation. It is considered a representation of a linguistic evaluation by two values named 2-tuple (t_i, α) where t_i is a term in the linguistic term set $T = \{t_0, t_1, ..., t_g\}$ and α is a numerical value that represents the symbolic translation. Tai and Chen [48] presented in their model the following two definitions.

Table 1. An extract of the quality coordinator competence framework.

Knowledge	Know the requirements of the ISO 9001 standard. Know external and internal stakeholder requirements, functional requirements, and quality performance requirements. Know the software dedicated to quality monitoring and control charts. Master the different quality tools (Amdec, Pareto chart, and others).
Know-how	Know how to formalize and adapt procedures/protocols/operating modes/instructions. Know how to raise awareness and train regularly the production teams on the different aspects of quality. Know how to determine and analyze quality indicators with the animation of daily monitoring meetings. Know how to manage non-conformities and monitor corrective and preventive actions.
Know-whom	Have good writing skills. Have a sense of analysis and reactivity. Be rigorous. Mastering group work.

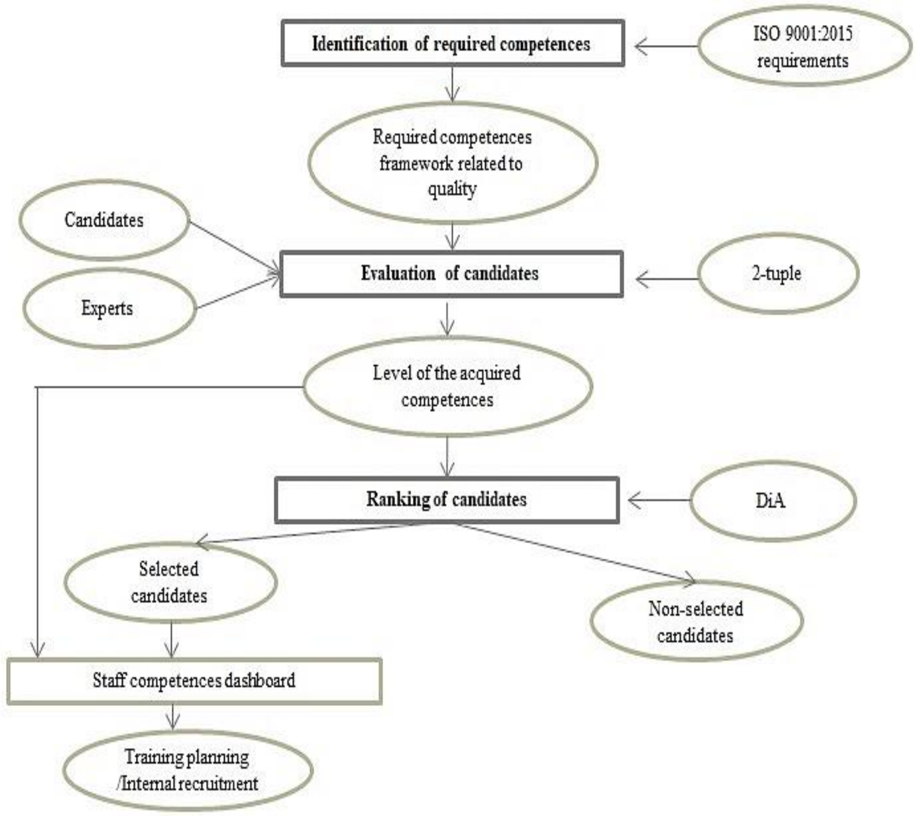

Fig. 1. The competencies assessment process related to quality.

Definition 1. There is a function Δ that defines the 2-tuple linguistic representation equivalent to the numerical value $\lambda \in [0,1]$ that represents the value resulting from a symbolic aggregation operation. It is defined as follows:

$$\Delta : [0,1] \rightarrow T \times \left[-\frac{1}{2g}, \frac{1}{2g}\right). \quad \textbf{(1)}$$

$$\Delta(\lambda) = (t_i, \alpha) \begin{cases} t_i & i = \text{round}(\lambda \times g). \\ \alpha = \lambda - \dfrac{i}{g}, & \alpha \in \left[-\frac{1}{2g}, \frac{1}{2g}\right). \end{cases}$$

Definition 2. There is a Δ^{-1} function that transforms the 2-tuple linguistic information into its equivalent numerical value λ.

$$\Delta^{-1} : T \times \left[-\frac{1}{2g}, \frac{1}{2g}\right) \rightarrow [0,1]. \quad \textbf{(2)}$$

$$\Delta^{-1}[t_i, \alpha] = \frac{i}{g} + \alpha = \lambda.$$

We chose the 2-tuple model to evaluate the level of competencies acquired by the staff or candidates because it is the most valuable and objective model to aggregate the experts' opinions by computing the initial linguistic information. Thus, it is the only model that allows us to translate the numerical result of the aggregation process into an equivalent linguistic term in the set $T = \{t_0, t_1, ..., t_g\}$ with the definition of the parameter that defines the translation value. This means that this model allows the results to be obtained accurately, without distortion of the initial information, and expressed in the same initial linguistic domain [49].

Table 2. The fuzzy evaluation scale.

Linguistic variable	Semantics
t_0 : None (N)	(0, 0, 0.17)
t_1 : Very Low (VL)	(0, 0.17, 0.33)
t_2 : Low (L)	(0.17, 0.33, 0.5)
t_3 : Medium (M)	(0.33, 0.5, 0.67)
t_4 : High (H)	(0.5, 0.67, 0.83)
t_5 : Very High (VH)	(0.67, 0.83, 1)
t_6 : Perfect (P)	(0.83, 1, 1)

Determination of candidates' acquired competencies levels using the 2-tuple representation model consists of three steps:

Step 1. Using the linguistic values described in *Table 2*, the experts evaluate the competencies acquired by each candidate.

Step 2. Transformation of each linguistic evaluation into 2-tuple information with consideration that $\lambda = 0$. Let us consider as an example the transformation of the low value (L) into $(t_2, 0)$.

Step 3. Aggregation of the experts' evaluations of each competence acquired by each candidate according to the following formula:

$$(t_{ij}, \alpha_{ij}) = \Delta\left(\frac{1}{k}\sum_{p=1}^{p=k}\Delta^{-1}\left(t_{ij}^{p}, \alpha_{ij}^{p}\right)\right), \tag{3}$$

where

${t_{ij}}^{p}$: evaluation of competence j $(j = 1, 2, \ldots\ldots, m)$ acquired by candidate i $(i = 1, 2, \ldots\ldots, n)$ provided by expert p $(p = 1, 2, \ldots\ldots, k)$.

${\alpha_{ij}}^{p}$: symbolic translation of the evaluation ${t_{ij}}^{p}$.

t_{ij} : aggregated evaluation of competence j acquired by candidate i.

α_{ij} : symbolic translation of the evaluation t_{ij}.

3.3 | Ranking of Candidates

Regarding the alternatives ranking process, the majority of researchers, such as Karim and Karmaker [50] and Chodha et al. [51], adopt the TOPSIS method developed by Hwang and Yoon [52], as it is the most practical and effective ranking method for in-depth data processing of complex decision-making problems. In short, it is considered the most coherent process for accurately ranking alternatives based on mathematical operations that take into account all expert evaluations and criteria weights without the need to determine additional technical parameters that generate additional costs for organizations to process the data with the risk of losing control of the original data.

Tran and Boukhatem [53] conducted a simulation of some ranking methods for a multi-criteria decision problem. They noticed that the TOPSIS method induces a "ranking anomaly" in the case of the elimination of a candidate. In other words, the ranking undergoes an abnormal change. To solve this problem, they proposed a new algorithm named DiA, which allows the ranking of candidates without generating a ranking anomaly. For this reason, we propose to integrate the 2-tuple model with the DiA method while developing a new approach to assessing candidates for quality positions by handling the subjectivity of qualitative evaluations.

The DiA algorithm is based on the calculation of the Manhattan distance between the levels of competencies acquired by a candidate and the positive and negative value of each competence instead of the Euclidean distance calculated in the TOPSIS method. Thus, it relies on the calculation of the Euclidean distance between each candidate and the best ideal candidate instead of the closeness coefficient of each candidate to the ideal solution calculated by the TOPSIS method. The algorithm of the DiA method consists of five steps:

Step 1. Normalization of the aggregate values calculated previously by the following formula:

$$N_{ij} = \Delta^{-1}\left(t_{ij}, \alpha_{ij}\right) / \sqrt{\sum_{i=1}^{i=n} \Delta^{-1}\left(t_{ij}, \alpha_{ij}\right)^2}. \tag{4}$$

Step 2. Weighting of the normalized values (calculated in the previous step) according to the following formula:

$$v_{ij} = N_{ij} \times w_j, \tag{5}$$

Where v_{ij} is the weighted evaluation of the competence j acquired by candidate i and w_j is the weight of competence.

Step 3. Calculation of two Manhattan distances, one that separates each candidate from the ideal positive solution and the other that separates it from the ideal negative solution, by using the following two formulas:

$$D_i^+ = \sum_{j=1}^{j=m} \left| v_{ij} - C_j^+ \right|. \tag{6}$$

$$D_i^- = \sum_{j=1}^{j=m} \left| v_{ij} - C_j^- \right|, \tag{7}$$

where

D_i^+ : distance of candidate i from the ideal positive solution.

C_j^+ : ideal positive solution of competence j.

D_i^- : distance of candidate i from the ideal negative solution.

C_j^- : ideal negative solution of competence j.

m: number of competences.

Step 4. Determination of the ideal positive alternative PIA.

The PIA is defined by

$$\min_i D_i^+ = \min \sum_{j=1}^{j=m} \left| v_{ij} - C_j^+ \right|. \tag{8}$$

$$\max_i D_i^- = \max \sum_{j=1}^{j=m} \left| v_{ij} - C_j^- \right|, \tag{9}$$

where $\min_i D_i^+$ is the minimum value of D_i^+ and $\max_i D_i^-$ is the maximum value of D_i^-.

Step 5. Determination of the ranking of the candidates.

The last step is to calculate the Euclidean distance between each candidate and the ideal positive alternative. This distance is calculated by using the following equation:

$$R_i = \sqrt{\left(D_i^+ - \min_i D_i^+\right)^2 + \left(D_i^- - \max_i D_i^-\right)^2}. \quad (10)$$

The ranking of candidates is provided according to the ascending order of R_i. This means that the best candidate is the one who has the shortest distance from the PIA.

4 | Case of Quality Coordinator Selection

Before each evaluation step, it is necessary to identify the evaluation criteria. For this reason, we have established a framework of competencies required of a quality coordinator by referring to the requirements of the 2015 version of the ISO 9001 standard [5], [54]. *Table 1* presents an extract of the quality coordinator competence framework that we have established.

Suppose that an organization desires to recruit a quality coordinator among five candidates (A_1, A_2, A_3, A_4 and A_5). We also suppose that the assessment will be based on six competencies (C_1, C_2, C_3, C_4, C_5 and C_6) and will be performed by four experts. In *Table 3*, we present the competencies weights that we have assumed.

Table 3. Competences weight.

Competence	Relative Weight
C_1	0.376
C_2	0.246
C_3	0.198
C_4	0.089
C_5	0.090
C_6	0.036

4.1 | Results

As a first step, each expert evaluates the level of competence acquired by each candidate using the linguistic values described in *Table 2*. The experts' evaluations are presented in *Table 4*. Then, the linguistic evaluations should be transformed into a 2-tuple representation and aggregated by *Eq. (3)*. The aggregate evaluations are presented in *Table 5*.

Table 4. The experts' evaluations.

	Expert 1					
Candidate	C_1	C_2	C_3	C_4	C_5	C_6
A_1	VL	H	M	P	L	H
A_2	M	M	H	VH	N	H
A_3	P	M	M	H	L	VH
A_4	VL	M	P	VL	M	P
A_5	P	M	H	VH	L	H
	Expert 2					
Candidate	C_1	C_2	C_3	C_4	C_5	C_6
A_1	N	M	VL	L	VL	L
A_2	L	M	M	M	M	M
A_3	H	M	H	M	M	P
A_4	M	H	VH	P	H	VH
A_5	P	VL	M	M	VL	VH

Table 4. Continued.

	Expert 3					
Candidate	C_1	C_2	C_3	C_4	C_5	C_6
A_1	N	N	M	M	M	H
A_2	M	H	H	H	H	M
A_3	VH	VH	L	VL	L	M
A_4	P	H	M	M	M	P
A_5	P	VL	M	H	M	M
	Expert 4					
Candidate	C_1	C_2	C_3	C_4	C_5	C_6
A_1	M	L	H	H	VH	M
A_2	L	P	H	M	H	H
A_3	H	M	M	H	L	VL
A_4	M	H	P	M	H	H
A_5	L	VL	M	H	L	P

According to *Eq. (4)* and *Eq. (5)*, we present in *Table 6* and *Table 7* the normalized and weighted evaluations of the candidates.

Table 5. The aggregated competence levels of the candidates.

Candidate	C_1	C_2	C_3	C_4	C_5	C_6
A_1	$(t_1, 0.0003)$	$(t_2, 0.04)$	$(t_3, -0.04)$	$(t_4, -0.04)$	$(t_2, 0.083)$	$(t_3, 0.042)$
A_2	$(t_2, 0.081)$	$(t_4, 0.0003)$	$(t_4, -0.039)$	$(t_4, -0.04)$	$(t_3, -0.04)$	$(t_4, -0.081)$
A_3	$(t_5, -0.04)$	$(t_3, -0.082)$	$(t_3, 0)$	$(t_3, 0.002)$	$(t_2, 0.038)$	$(t_4, -0.04)$
A_4	$(t_3, 0.042)$	$(t_4, -0.04)$	$(t_5, 0.0013)$	$(t_3, 0.024)$	$(t_4, 0.081)$	$(t_5, 0.04)$
A_5	$(t_5, -0.001)$	$(t_2, -0.081)$	$(t_3, 0.042)$	$(t_4, -0.039)$	$(t_2, -0.001)$	$(t_4, 0.04)$

Table 6. Normalized levels of acquired competencies.

Candidate	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.124	0.319	0.339	0.476	0.442	0.357
A_2	0.308	0.568	0.462	0.476	0.465	0.386
A_3	0.588	0.495	0.368	0.382	0.376	0.412
A_4	0.402	0.532	0.613	0.413	0.592	0.577
A_5	0.618	0.214	0.399	0.478	0.336	0.468

Table 7. Weighted levels of acquired competencies.

Candidate	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.046	0.078	0.067	0.042	0.039	0.012
A_2	0.115	0.139	0.091	0.042	0.041	0.013
A_3	0.221	0.121	0.072	0.033	0.033	0.014
A_4	0.151	0.129	0.121	0.036	0.053	0.02
A_5	0.232	0.052	0.079	0.042	0.03	0.016

In *Table 8*, we present the positive and negative distances of the candidates which are calculated by *Eq. (6)* and *Eq. (7)*. In the same table, we determine the ideal positive alternative PIA according to *Eq. (8)* and *Eq. (9)*, and we also show the final ranking of the candidates according to *Eq. (10)*. In *Table 9*, we present the cases of elimination of a candidate from the list of candidates.

Table 8. Candidates' ranking obtained by the DiA method.

Candidate	D_i^+	D_i^-	R_i	**Rank**
A_1	0,323	0,044	0,319	5
A_2	0,166	0,201	0,097	4
A_3	0,113	0,254	0,022	2
A_4	0,097	0,27	0	1
A_5	0,156	0,211	0,083	3
PIA	0,097	0,27		

Table 9. Ranking result after the elimination of a candidate.

The case of the elimination of candidate A_1				
Candidate	D_i^+	D_i^-	R_i	**Rank**
A_2	0,166	0,126	0,097	4
A_3	0,113	0,179	0,022	2
A_4	0,097	0,195	0	1
A_5	0,156	0,136	0,083	3
PIA	0,097	0,195		
The case of the elimination of candidate A_4				
Candidate	D_i^+	D_i^-	R_i	**Rank**
A_1	0,277	0,044	0,296	4
A_2	0,12	0,201	0,074	3
A_3	0,067	0,254	0	1
A_5	0,11	0,211	0,06	2
PIA	0,067	0,254		
The case of the elimination of candidate A_5				
Candidate	D_i^+	D_i^-	R_i	**Rank**
A_1	0,312	0,015	0,372	4
A_2	0,155	0,172	0,155	3
A_3	0,102	0,225	0,087	2
A_4	0,086	0,241	0	1
PIA	0,086	0,241		

Finally, we applied our example with the TOPSIS method in order to make a comparative study between this method and the DiA method, considering the 2-tuple evaluation result (*Table 5*) as the input of the ranking process. *Table 10* presents the application result of the TOPSIS method in our example.

Table 10. Results of candidates' ranking by the TOPSIS method.

	Initial result		Elimination of candidate A_1		Elimination of candidate A_4		Elimination of candidate A_5	
Candidate	R_i	**Rank**	R_i	**Rank**	R_i	**Rank**	R_i	**Rank**
A_1	0,121	5			0,124	4	0,049	4
A_2	0,485	4	0,426	4	0,493	2	0,461	3
A_3	0,767	1	0,688	1	0,385	3	0,762	1
A_4	0,638	3	0,554	2			0,65	2
A_5	0,652	2	0,541	3	0,678	1		

In summary, we consolidate the results in *Table 11* to enable a thorough comparative analysis of the TOPSIS and DiA methods.

Table 11. Results of candidates' ranking by the TOPSIS method and DiA method.

	Weighted Levels of Acquired Competencies						Rank DiA	Rank TOPSIS	Elimination of Candidate A_1		Elimination of Candidate A_4	
	C_1	C_2	C_3	C_4	C_5	C_6			Rank DiA	Rank TOPSIS	Rank DiA	Rank TOPSIS
A_1	0.046	0.078	0.067	0.042	0.039	0.012	5	5			4	4
A_2	0.115	0.139	0.091	0.042	0.041	0.013	4	4	4	4	3	2
A_3	0.221	0.121	0.072	0.033	0.033	0.014	2	1	2	1	1	3
A_4	0.151	0.129	0.121	0.036	0.053	0.02	1	3	1	2		
A_5	0.232	0.052	0.079	0.042	0.03	0.016	3	2	3	3	2	1

4.2 | Discussion

In the context of our illustrative example, we can demonstrate that our 2-tuple DiA approach constitutes the optimal solution for a company seeking to assess and select the most competent candidates without distorting the linguistic evaluations of the assessors. Firstly, the 2-tuple aggregation operator stands out as the optimal choice for obtaining the most reasonable aggregation results.

Let's take the example of candidate A_1, assessed by two experts with moderate and low levels of competence in C_1, while two other asse ssors believe that he has not acquired competence C_1 at all. Upon examining *Table 5*, which presents the evaluation values aggregated by the 2-tuple aggregation operator *Eq. (5)*, we observe that candidate A_1 obtained an aggregated value in the form of a 2-tuple $(T_1, 0.0003)$, indicating a very low level of competence in C_1. This alignment with the initial judgments of the assessors enhances the credibility of the obtained results. Continuing with the example of A_1, we note that two assessors evaluated his level of competence C_6 as high, while two others assessed it as having a moderate and low level for this competence. Revisiting *Table 5*, candidate A_1 obtains an aggregated evaluation value in the form of $(T_3, 0.042)$, signifying a moderate level of competence C_6. This finding confirms the effectiveness of the 2-tuple aggregation operator in gathering and aggregating expert evaluations while preserving the initial evaluations.

Similarly, we will now demonstrate the feasibility and validity of the DiA method for the selection of competent candidates. Consider the example of the two competencies C_2 and C_5, as shown in *Table 7*, their

best negative ideal solutions C_2^{-old} and C_5^{-old} are 0.052 and 0.03, respectively, and which are the values of candidate A_5. Suppose this candidate is removed from the list of candidates; the new negative ideal solutions C_2^{-new} and C_5^{-new} become 0,078 and 0,033, respectively. If we suppose that there is a distance G between the old and the new ideal negative solution, then this distance will be calculated according to the following formula

$$G = \left|C_2^{-new} - C_2^{-old}\right| + \left|C_5^{-new} - C_5^{-old}\right| = 0.029. \quad \textbf{(11)}$$

In *Table 9*, we can see that after eliminating candidate A_5, all the distances D_i^- of the candidates were decreased by 0.029 from their initial values. In the same way, the distance $\max_i D_i^-$ of the ideal alternative PIA was decreased by the same value. Following the same case of eliminating candidate A_5, the ideal positive solution C_1^+ was changed from 0.232 to 0.221. Therefore, all distances D_i^+ were decreased from their initial values by a value $F = 0.011$. Thus, the distance $\min_i D_i^+$ of the ideal alternative PIA was decreased by the same value.

The Manhattan distance changes the distances D_i^- and D_i^+ of the alternatives uniformly. According to our example, in the case of eliminating candidate A_5, all the distances D_i^- of the candidates are decreased by a value $G = 0.029$, which is defined as the distance or gap value that exists between the old and the new negative ideal solution. Furthermore, we can see that all distances D_i^+ of the candidates are decreased by a value $F = 0.011$, which is defined as the distance or gap value that exists between the old and the new positive ideal solution. For this reason, as shown in *Table 9*, despite the elimination of candidate A_5, the ranking of the candidates remained unchanged. The same table shows that when one of the other candidates was eliminated, the ranking of the candidates was not changed.

From *Table 8* and *Table 9*, which show the result of applying the DiA method in our quality coordinator selection example, and *Table 10,* which shows the result of applying the TOPSIS method, we can observe and conclude that:

I. Candidates A_1 and A_2 were ranked the fifth and fourth best candidates by both methods, while candidates A_3, A_4, A_5 and were ranked 2nd, 1st, and 3rd by the DiA method and 1st, 3rd, and 2nd by the TOPSIS method. Returning to *Table 6*, we see that candidate A_3 has a lower level of competence C_1 than candidate A_5, with a difference of 0.011, but has a high level of competence C_2 compared to the level of candidate A_5, with a difference of 0.087. For competence C_3, which is less important than competence C_2, there is a slight difference (equal to 0.007) between the levels of candidate A_3 and candidate A_5. These candidates (A_3 and A_5) have almost the same level of competence C_5. However, candidate A_5 has two higher levels of competence C_4 and competence C_6 than candidate A_3; However, according to *Table 3*, these are the two least important competencies. Therefore, it is clear that candidate A_3 is better than candidate A_5. This analysis result allows us to conclude that the DiA method ranks the candidates more precisely than the TOPSIS method without distorting the experts' initial evaluations.

II. According to the three simulations (elimination of candidates A_1, A_4 and A_5) that we carried out, we noticed that the ranking obtained with the TOPSIS method changes when a candidate is eliminated. On the other hand, with the DiA method, the ranking remains stable each time a candidate is eliminated.

In order to generalize the interest and effectiveness of our approach, we established *Table 11*, allowing us to analyze the ranking of candidates using the TOPSIS method on the one hand and the DiA method on the other. This comparison aims to validate our approach. *Table 11* presents the normalized and weighted evaluations of the candidates' acquired levels, considered as inputs for both TOPSIS and DiA methods.

The analysis of the initial ranking results of the candidates, as discussed in the preceding paragraphs, confirms the justification of the initial ranking assigned to candidate A_4 by the DiA method rather than ranking A_3 in the first position. This observation extends to all candidates. However, an additional observation in *Table 11* draws attention. With each elimination of a candidate from the final ranking list, the TOPSIS method exhibits an unreasonable change in the ranking of candidates. For instance, after eliminating candidate A_1, candidate A_5, initially ranked second, becomes third, and candidate A_4, initially ranked third, moves to the second

position. These results raise doubts about the reliability of the ranking outcomes obtained through the TOPSIS method. Conversely, the DiA method maintains the final ranking unchanged even when a candidate is eliminated. When eliminating candidate A_1, all other candidates retain their original ranking order. Similarly, in the case of eliminating candidate A_4, all candidates maintain their initial order. This consistency in ranking, unlike the TOPSIS method, enhances the reliability of the results obtained through the DiA method.

Finally, we can conclude that our approach allows:

III. The evaluation of candidates with precision while preserving the initial information and treating the subjectivity of the experts' evaluations, using the 2-tuple representation model.

IV. The final results to be expressed in the same initial linguistic style of the experts by using the 2-tuple representation model.

V. The ranking of candidates using the DiA method retains the initial information and maintains the final ranking even if a candidate is eliminated from the candidate list.

VI. The creation of a dashboard that represents the level of competencies acquired by recruits and employees represented as 2-tuple linguistic values. The Acquired Competencies Dashboard allows organizations to identify their competence needs, facilitate internal recruitment, and create appropriate employee training plans.

5 | Conclusion

The management of competencies is an essential management tool for companies that want to improve their performance and achieve competitive advantages. In this work, we are interested in the evaluation and classification of competencies in the field of quality. For this purpose, we have developed a new framework of competencies required by a quality coordinator in accordance with the requirements of the latest version 2015 of the ISO 9001 standard. We have also developed a new approach for the assessment of competencies related to quality, based on the integration of the linguistic model 2-tuple with the DiA method. With this approach, organizations can:

– *Evaluate the acquired competencies of personnel using the 2-tuple representation model.*
– *Facilitate interviews and select qualified candidates.*
– *Avoid job discrimination.*
– *Identify gaps between the required and acquired competencies to determine the necessary training plans.*
– *Form project groups based on the Acquired Competences Dashboard.*

This study aims to propose, for the first time, an approach to assess the competencies related to the quality field. As a perspective, we will experiment with this model in a company that wishes to recruit internally or externally a qualified quality coordinator whose position plays an essential role in QMS management. For the future validation of the proposed fuzzy method, delving into a broader range of cases and conducting more in-depth empirical studies could prove helpful.

This study also had certain limitations. First, we used a numerical example to demonstrate the applicability of the method. However, the incorporation of real and more complete data, particularly concerning the number of competencies or the number of candidates, can introduce increased complexity to the work. Therefore, it is recommended that researchers apply the method to more relevant data or develop appropriate computer tools for application in real recruitment situations. Secondly, while we have focused on the limitations of the TOPSIS method, by addressing them through the development of a new approach based on the integration of the DiA method with a 2-tuple representation, it is possible to discover more precise methods in the field of multicriteria decision-making. Therefore, it is suggested that future research should focus on comparing the 2-tuple DiA method with other multicriteria decision-making techniques.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

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